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Image Restoration Using Group-based Sparse Representation Technique

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Abstract— *This paper presents an efficient algorithm for solving restoration problem in the frame-based image restoration. In image restoration, the patch-based approach has been used for better results without degrading the image. Our proposed procedure for solving the stable optimal problem is based on a patched group strategy method. In this paper GSR (Group Based Sparse Representation) algorithm is proposed which is based on concept that group of patches are constructed which maintains the relationship among various patches of images and it is implemented for three image restoration problems i.e. DE noising, DE blurring and Image enhancement. Various parameters are taken into account like PSNR, SSIM, speed and time. The simulation experiments have been conducted in MATLAB and the results have been compared with existing scheme i.e. patch based sparse representation. Both standard and real time images have been included in simulation. It has been observed that after the reconstruction of an image values of parameters are increased which are more than existing scheme.*

Keywords—Analysis-based approach, Group-based patches, Image enhancement, Image Restoration, Patch method.

I. INTRODUCTION

Image restoration may be declared as method within which the prime quality image is fixed up from the degraded caliber image. It is an associate degree operation within which a corrupt/noisy image is taken and also the clean, original image is calculated. Corruption could take several forms like camera miscues, part turbulence and camera or object motion etc. In image restoration the transpose operations of activity is done which produces blur in the image to get the original image back. The information that is corrupted due to blurring can be get back with the help of Point Spread Function (PSF).

Image restoration and image improvement each area unit completely different in sense that the latter is meant to emphasize varied options of the image so as to supply the additional pleasing image to the observer.

Noise will effectively be removed by ignoring some resolution in image improvement. However this can be not acceptable in several applications like during a visible radiation magnifier, resolution within the z-direction is dangerous. Image restoration techniques are area unit enforced with objective of reducing noise and convalescent resolution loss. These techniques area unit performed in 2 domains either within the image domain or the frequency domain. In American state convolution technique noise is absent which the blurring method is shift-invariant and therefore it introduces additional subtle techniques to manage the various varieties of noises and blurring functions.

Applications of Image restoration

- Denoising and artifacts removal
- Sharpness, contrast and resolution enhancement
- In medical images (CT, MRI, ultrasound, etc.)
- HD/3D/mobile displays, web-scale data, legacy materials etc.

DE noising Techniques

When the only degradation present in an image is noise, then equation becomes

$$g(x, y) = f(x, y) + \eta(x, y) \quad (1)$$

$$\text{And, } G(u, v) = F(u, v) + N(u, v) \quad (2)$$

DE noising techniques exist in each spatial domain in addition as frequency domain.

Spatial Filtering: Spatial filtering is most popular once solely additive noise is gift. The different categories of filtering techniques exist in spatial domain filtering. During this technique, the center pixel worth of the filter window is replaced with the first moment of all the pixel values among the filter window. Noise is reduced as results of this smoothening however edges among the image get blurred.

Median Filter: Median filter belongs to the category of order-statistics filters. The ordering of pixels contained within the filter window is that the response of those filters. Median filter replaces the worth of a pixel by the median of the grey levels among the filter window.

Adaptive Filter: For the removal of impulse noise from an image the adaptive filtering uses the gray and color space. Gray and color space is the base for the whole processing in adaptive filtering. Best noise prevention results can be provided by it and better preserve thin lines, the image edges and the image details. As compared to other filters it provides better image quality.

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II. PREVIOUS FINDINGS

Guo and An [1] have presented a brand new restoration algorithmic rule that implements the filling of broken region with morphological erosion and propagates structure/texture options of the best-known region into the broken region with exemplar-based texture synthesis. The strategy will retain the continuity of image isopods between the best-known region and therefore, the repaired broken region, and output an entire, natural looking image. Through comparative experiments with some existing ways, we tend to demonstrate the effectiveness of the algorithmic rule in removing giant objects similarly as skinny scratches.

Zhang et al. [2] have proposed fuzzy genetic algorithmic rule (FGA) on the premise of genetic algorithmic rule. Uncertainty issues may be resolved within the method of image process by constructing fuzzy characteristic matrix and fuzzy fitness perform, and victimization fuzzy genetic improvement technique. Huan et al. [3] have proposed Associate in Nursing economical image in painting algorithmic rule by introducing vital aspects and enhancements admire the filling order of the pixels within the target region and texture synthesis in an exceedingly dynamic looking vary. The algorithmic rule is easy to implement and restores the target regions with visually plausible quality *i.e.* higher than many existing ways with a lower execution price.

Wang et al. [4] have presented a unique image super-resolution technique supported learning the distributed association between input image patches and therefore, the example image patches. We tend to improve Associate in Nursing existing distributed-coding algorithmic rule to search out sparse association between image patches. Dharmarajan and Kannan [5] have designed an algorithm for the hypergraph (HG) representation of an image, subsequent detection of Salt and Pepper (SP) noise in the image and finally the restoration of the image from this noise. The proposed algorithm exhibits superiority over traditional algorithms and recently proposed ones in terms of visual quality, Peak Signal to Noise Ratio (PSNR) and Mean Absolute Error (MAE).

Yang et al. [6] have introduced the concept of examples-aided redundant dictionary learning into the single-image super-resolution reconstruction, and have proposed multiple dictionaries learning scheme inspired by multitask learning, in order to avoid a large training patches database and obtain more accurate recovery of HR images. Chen et al. [7] have designed a new sparsity-based algorithm for the classification of hyper spectral imagery. The proposed algorithm relies on the observation that a hyper spectral pixel can be sparsely represented by a linear combination of a few training samples from a structured dictionary. Giannoula et al.[8] have proposed, the blind restoration of a scene, when multiple degraded (blurred and noisy) acquisitions are available. An adaptive filtering technique is proposed, where the distorted images are filtered, classified and then fused based upon the classification decisions.

III. PROPOSED WORK

The objective of image restoration technique is to scale back noise and recover resolution loss. Image processing techniques are performed either within the image domain or the frequency domain. The most common and simple technique for image restoration is DE Convolution, that is performed within the frequency domains. DE convolution technique because of its direct inversion of PSF amplifies noise and creates the resulting image which is imperfectly deblurred. Therefore, additional subtle techniques are developed to recover the various forms of noises and blurring functions.

Image processing uses various kinds of filtering techniques like Median filtering, Linear Filtering and adaptation Filtering etc to view a picture to its original forms.

Operations on original images

Now for restoring the image which is approximately similar to original image from the degraded image we have to perform following operations on degraded image.

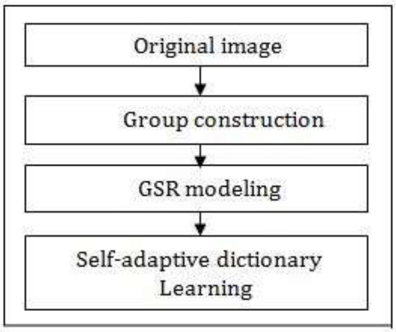

Fig.1: Operations on original image

1. Group Construction

The group construction is carried out by following the steps described below:

Step 1: Divide the image x with size N into n overlapped patches of size $\sqrt{B_s} \times \sqrt{B_s}$ and each patch is denoted by the vector $x_k \in \mathbb{R}^{B_s}$ i.e., where k = 1, 2 …, n.

Step 2: For each patch x_k within the training window of size $L \times L$, search its c best matched patches which contain the set S_{x_k} . Euclidian distance is used to find out the similarity between the different patches.

Step 3: All the patches in the set S_{x_k} are put into a matrix of size$B_s \times c$, denoted by $x_{G_k} \in \mathbb{R}^{B_s \times c}$, which includes every patch in S_{x_k} as its columns, i.e., x_{G_k} =

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$\{x_{G_k\otimes 1}, x_{G_k\otimes 2}, \ldots, x_{G_k\otimes c}\}$. The matrix x_{G_k} is called as group. This can be represented by equation as:

$$x_{G_k} = R_{G_k}(x) \tag{3}$$

Where, R_{G_k} (.) is the operator which is used to extract the group x_{G_k} from x, and its transpose, $R^T{}_{G_k}$(.), can put back a group into its kth position in the reconstructed image, padded with zeros elsewhere. Thus one can recover whole image x from $\{x_{G_k}\}$ become:

$$x = \sum_{k=1}^{n} R_{G_k}^T \left(x_{G_k}\right) ./ \sum_{k=1}^{n} R_{G_k}^T \left(1_{B_{S\times C}}\right) \tag{4}$$

Where, ./ represents element-wise division of the two vectors and $1_{B_{S\times C}}$ represents matrix of size $B_s \times c$ with all element being 1.

2. Group-Based Sparse Representation Modeling

The GSR model assumes that by using few atoms of the self-adaptive learning dictionary D_{G_k} each group x_{G_k} can be represented accurately. Thus,

$D_{G_k} = \{d_{G_k\otimes 1}, d_{G_k\otimes 2}, \ldots, d_{G_k\otimes m}\}$ is supposed to be known. D_{G_k} is of size $(B_s \times c) \times m$, that is, $D_{G_k} \in \mathbb{R}^{(B_s\times c)\times m}$.

The rationale behind the sparse coding process of every group is to seek sparse vector $\alpha_{G_k} = [\alpha_{G_{k\otimes 1}}, \alpha_{G_{k\otimes 2}} \ldots\ldots, \alpha_{G_{k\otimes m}}]$,

such that, $x_{G_k} = \sum_{i=1}^{m} \alpha_{G_{k\otimes i}} d_{G_{k\otimes i}}$. For simplicity here $D_{G_k}\alpha_{G_k}$ is used to represents $\sum_{i=1}^{m} \alpha_{G_{k\otimes i}} d_{G_{k\otimes i}}$.

After this, the whole image can be sparsely represented by the $\{\alpha_{G_k}\}$ that is the set of the sparse codes. Thus, x can be constructed from $\{\alpha_{G_k}\}$ which can be represented by

$$x = D_G \circ \alpha_G \stackrel{\text{def}}{=} \sum_{k=1}^{n} R_{G_k}^T (D_{G_k}\alpha_{G_k}) ./ \sum_{k=1}^{n} R_{G_k}^T \left(1_{B_{S\times C}}\right) \tag{5}$$

Where D_G denotes the concatenation of all D_{G_k}, and α_G denotes the concatenation of all α_{G_k}.

3. Self-Adaptive Group Dictionary Learning

While learning the dictionary for each group following points must be considered.

1) Computational cost must be minimized.

2) The learnt dictionary must be adaptive for a group that is all the groups$\{x_{G_k}\}$are represented by the same dictionary D_{G_k}.

3) It must consider the characteristics of each group x_{G_k}, containing the patches with similar patterns.

The adaptive dictionary for each group is directly learnt from its estimate r_{Gk} which is naturally selected in the process of optimization. After obtaining r_{Gk}, apply SVD. This can be formulated as follows:

$$r_{G_k} = U_{G_K} \Sigma_{G_k} V_{G_k}^T = \sum_{i=1}^{m} \gamma r_{G_{k\otimes i}} \left(U_{G_{k\otimes i}} U_{G_{k\otimes i}}^T\right) \tag{6}$$

Where, $\gamma_{r_{G_k}} = [\gamma_{r_{G_{k\otimes 1}}}; \gamma_{r_{G_{k\otimes 2}}}; \ldots; \gamma_{r_{G_{k\otimes m}}}]$ $\Sigma_{G_k} = diag(\gamma_{r_{G_k}})$ is a diagonal matrix with elements on its main diagonal and $u_{G_{k\otimes i}}, v_{G_{k\otimes i}}$ are the columns of U_{G_K} and V_{G_K}.

For the group x_{G_k}, each atom in dictionary D_{G_k} is defined as,

$$d_{G_k\otimes i} = u_{G_{K\otimes i}} v_{G_{k\otimes i}}^T, \quad i = 1, 2\ldots\ldots, m, \tag{7}$$

Where, $d_{G_k\otimes i} \in \mathbb{R}^{B_s\times c}$. Thus, the learned dictionary for the group x_{G_k} is given by:

$$D_{G_k} = [d_{G_k\otimes 1}, d_{G_k\otimes 2}, \ldots, d_{G_k\otimes m}] \tag{8}$$

Operations on degraded image

Now for restoring the image which is approximately similar to original image from the degraded image we have to perform following operations on degraded image.

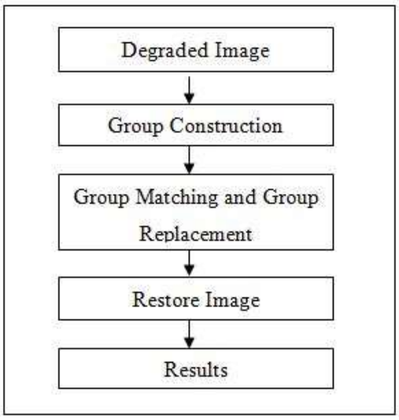

Fig.2: Operations on degraded image

1. Group Construction

Similar procedure which we applied on original image for group construction is carried out on degraded images too and the groups are constructed.

2. Group Matching and Group Replacement

In group matching the constructed group of degraded image is compared and matched with the constructed group of original image. After the group is matched the group of degraded image is replaced with the group of original image.

3. Restored Image

After replacing all the groups of the degraded image we get the restored image which is approximately similar to the original image.

IV. EXPERIMENATL RESULTS

The datasets has been obtained from controlled forms. The controlled dataset has been obtained on the similar background, which may offer the utmost accuracy. The information collected within the ideal conditions has well-tried to be the foremost economical information in terms of accuracy. The controlled information has been collected from the assorted objects (persons).

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Fig.3: Test Images (a) House (b) Cameraman (c) Vegetables

Performance Evaluation Parameters

SSIM: SSIM is used for measuring the similarity between two images. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

PSNR: Peak signal-to-noise ratio is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not.

MSE: In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator measures the average of the squares of the errors or deviations, that is, the difference between the estimator and what is estimated.

Evaluation measures for Denoising

(a)SSIM

De-noising has been tested for 12 Images from standard dataset used in existing scheme. The average SSIM value has been taken from all 12 images. Final Values are shown with the line increasing upwards.

Table.1: SSIM measures

Sr.	SSIM
1	0.1787
2	1.5416
3	1.7087
4	1.7644
5	1.8754
6	1.8773

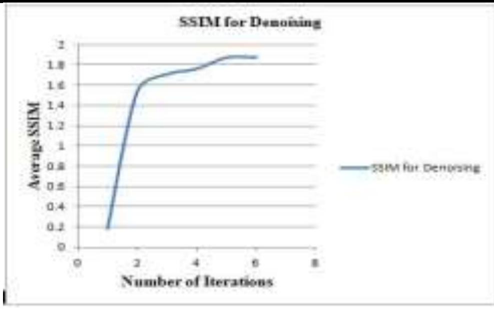

Fig.4: SSIM values on a graph for no. of iterations

(b) PSNR

PSNR values are evaluated for both existing method and proposed method. Average values are obtained with different sigma values.

Table.2: PSNR values in MS-EPLL

Sigma	MS-EPLL
15	29.01
25	28.23
50	30.16
100	23.8

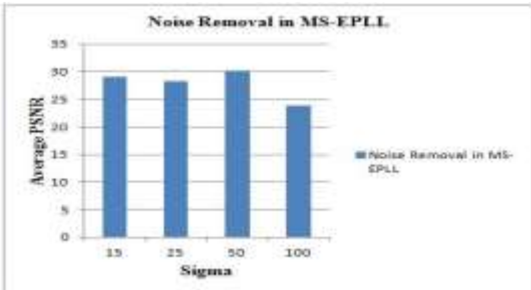

Figure.5 Different values of PSNR for different values of sigma.

De-noising has been tested for 12 Images from standard dataset used in existing scheme. The average PSNR value has been taken from all 12 images. This graph shows the average PSNR values for corresponding values of sigma.

Table.3: PSNR values in GSR

Sigma	GSR
15	34
25	32
50	28
100	25.6

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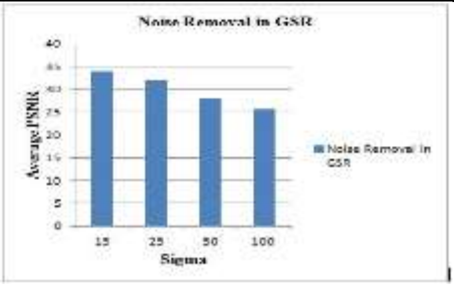

Fig.6: Different values of PSNR for different values of sigma.

De-noising has been tested for 12 Images from standard dataset used in existing scheme. The average PSNR value has been taken from all 12 images. This graph shows the average PSNR values for corresponding values of sigma.

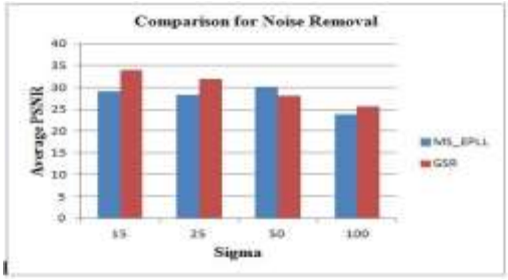

Fig.7: comparison of PSNR values for existing and proposed method

There is comparison between results of existing and proposed algorithm namely, GSR and MS-EPLL for average PSNR in De-noising process with different sigma values. De-noising has been tested for 12 Images from standard dataset used in existing scheme. The average PSNR value has been taken from all 12 images. Final Values has been compared with existing scheme. Proposed model shows the better results in comparison of existing scheme.

(C) SPEED

This graph shows how much speed is measured while implementing GSR algorithm during noise removal.

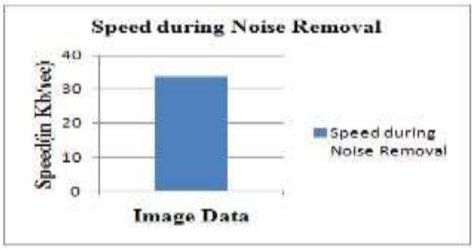

Fig.8: Average Speed for different images

(d) TIME

The graph below sows time taken while implementing GSR algorithm for Noise removal.

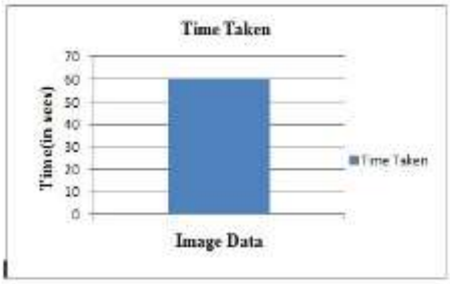

Fig.9: Time taken for different images

Evaluation Measures for Image Enhancement

Image Enhancement has been tested on 12 Images from standard dataset used in existing scheme. The average PSNR value has been taken from all 12 images. Final Values has been compared with existing scheme. Proposed model shows the better results in comparison of existing scheme.

(a) PSNR

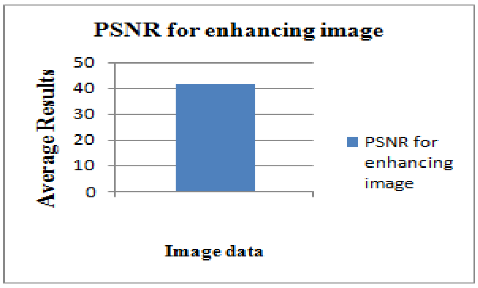

Fig.10: Average PSNR for different images

This graph shows the average PSNR value while enhancing image for different images selected from standard dataset.

(b) MSE

Image Enhancement has been tested on 12 Images from standard dataset used in existing scheme. The average MSE value has been taken from all 12 images. It shows better results in proposed algorithm.

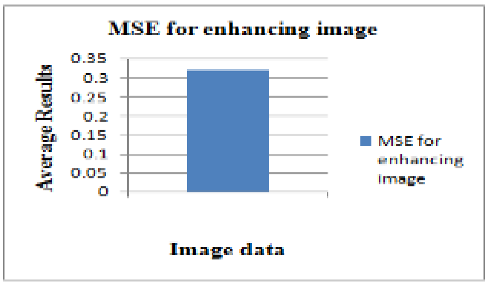

Fig.11: Average MSE for different images

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(C) SPEED

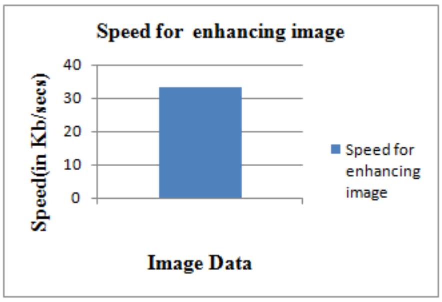

Fig.12: Average speed for different images

This graph shows how much speed is measured while implementing GSR algorithm for image enhancement.

(d) TIME

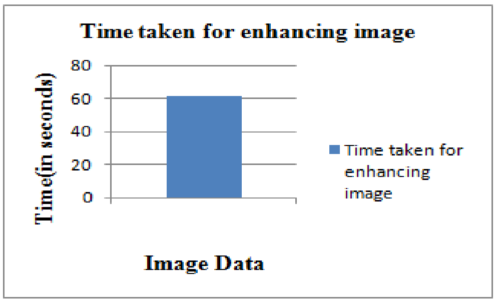

Fig.13: Average speed for different images

This graph shows the time taken for processing an image during image enhancement and it shows better results.

Evaluation Measures for Deblurring

(a) PSNR

PSNR is usually expressed in terms of the logarithmic decibel scale. The signal in this case is the original data, and the noise is the error introduced by compression.

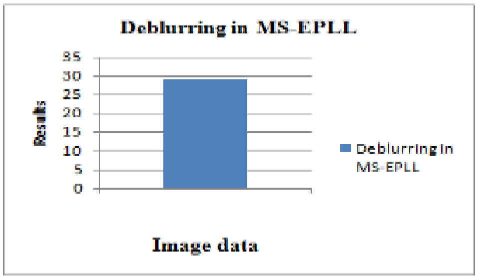

Fig.14: Average PSNR values for different images in existing system

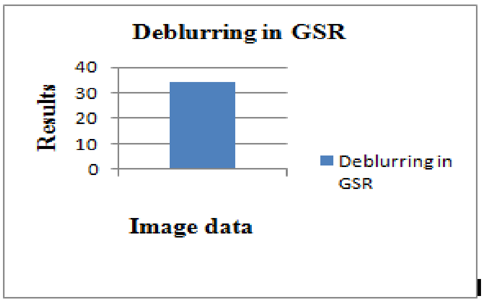

Fig.15: Average PSNR values for different images in proposed system

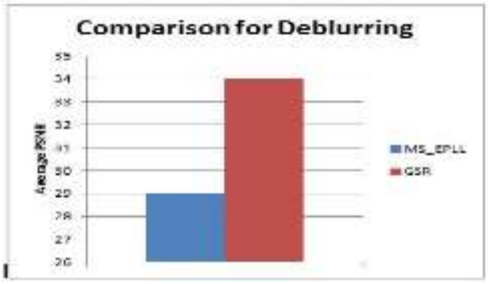

Fig.16: Comparison between existing system and proposed system on the basis of PSNR values

Deblurring has been tested for 12 Images from standard dataset used in existing scheme. The average PSNR value has been taken from all 12 images. Final Values has been compared with existing scheme. Proposed model shows the better results in comparison of existing scheme.

(C) SPEED

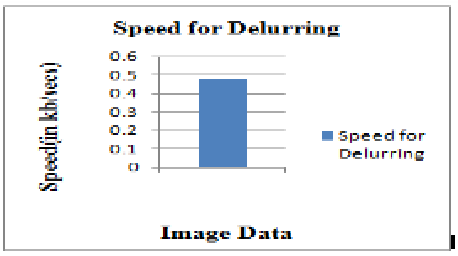

Fig.17: Average speed for different images

This graph shows how much speed is measured while implementing GSR algorithm for image enhancement.

(d) TIME

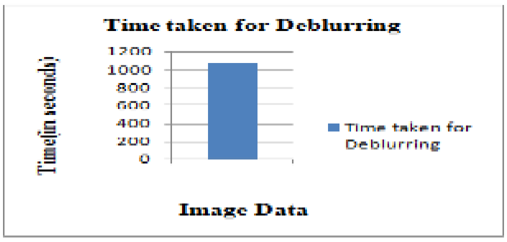

Fig.18: Time taken for different images

This graph shows the time taken for processing an image during image enhancement and it shows better results.

V. CONCLUSION & FUTURE WORK

In this paper GSR (Group Based Sparse Representation) algorithm is proposed which is based on concept that group of patches are constructed which maintains the relationship among various patches of images and it is implemented for three image restoration problems *i.e.* DE noising, DE blurring and Image enhancement. Various parameters are taken into account like PSNR, SSIM, speed and time. In Future, this research could be improved for fasten the results. Working upon speed for the system could further enhance this research/ technique. Also this research could be further implemented on various applications for image restoration. Now the GSR technique has very slow rate for image restoration, which takes lots of time to produce the results. This technique could also be designed without taking the original image for restoration.

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